Deep learning models for brain imaging
model depth enhances discovery power

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Lovelace
The University of New Mexico

joint work with Devon Hjelm, Ruslan Salakhutdinov, Jeremy Bockholt, Jeffrey Long, Hans Johnson, Jane Paulsen Jessica Turner and Vince D. Calhoun

Why deep learning

- Deep learning was created for automatic representation[1]:
  - roots in artificial neural nets (representation machines)
  - can work in generative mode
  - learn from the data (feature selection not required)
- Deep learning is beating records in pattern recognition:
  - natural image classification[2]
  - street sign recognition (superhuman performance)
  - for more see `http://tinyurl.com/os3xnpb`
- Widely successful in commercial pattern recognition
  - Google's Deep Brain division
  - Facebook's deep learning department
  - Microsoft, Amazon, Yahoo, Baidu, etc.
- Extensive press coverage: New York Times (twice!), Wired...
- Not yet widely used in natural sciences
- Until recently (are we the first?), close to zero use in neuroimaging

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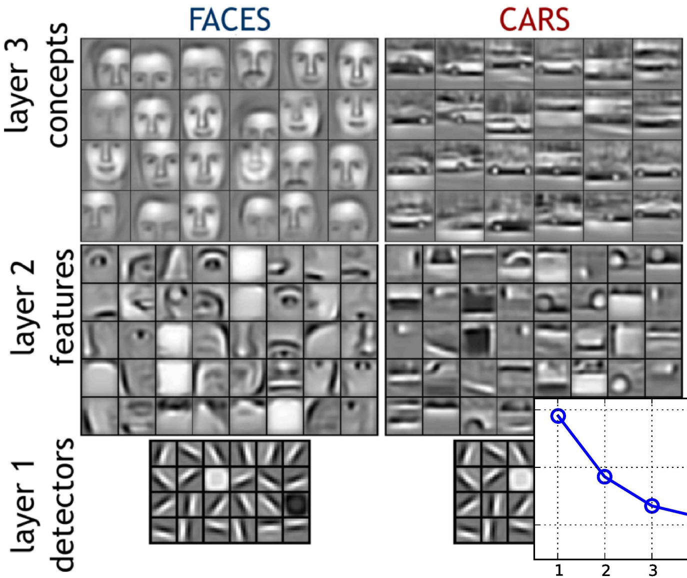
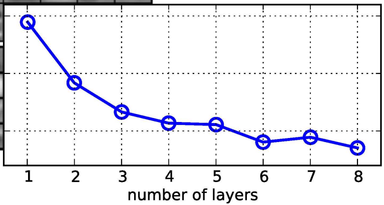
What is deep learning (a biased view)



- a powerful probabilistic building block
- a superior classifier
- depth increases modeling power
- an excellent representation learner



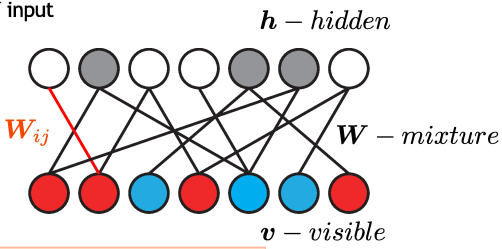
Does it hold on neuroimaging data?

Restricted Boltzmann Machine (RBM)

GOAL — estimate the joint distribution of input and hidden variables

PROXY — estimate θ that maximizes the probability that the model assigns to the data

$$\mathrm{agrmax}_\theta \prod_{v \in \boldsymbol{V}} P(v)$$



MODEL

parameters

$$\theta = \{\boldsymbol{a}, \boldsymbol{b}, \boldsymbol{W}\}$$

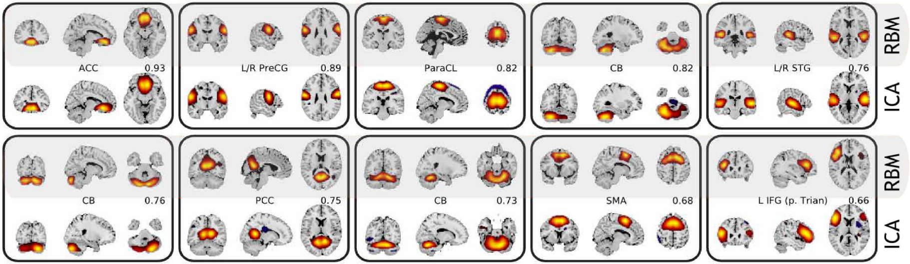
joint distribution

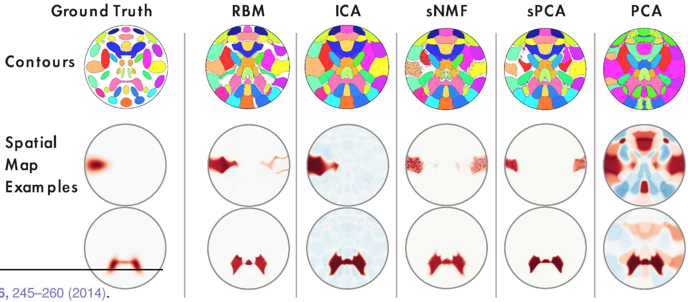
$$P(\boldsymbol{v}, \boldsymbol{h}; \theta) = \frac{1}{Z(\theta)} \exp(-E(\boldsymbol{v}, \boldsymbol{h}; \theta))$$

Gibbs energy

$$E(\boldsymbol{v}, \boldsymbol{h}; \theta) = -\sum_{i=1}^{V} \sum_{j=1}^{H} v_i W_{ij} h_j - \sum_{i=1}^{V} a_i v_i - \sum_{j=1}^{H} b_j h_j$$

RBM learns useful representations[3]





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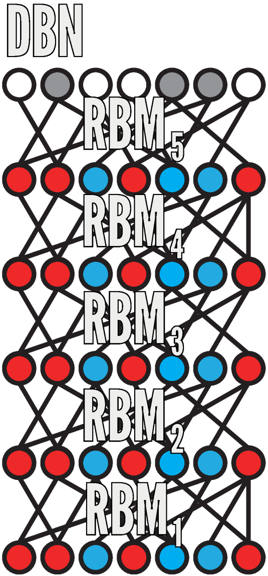
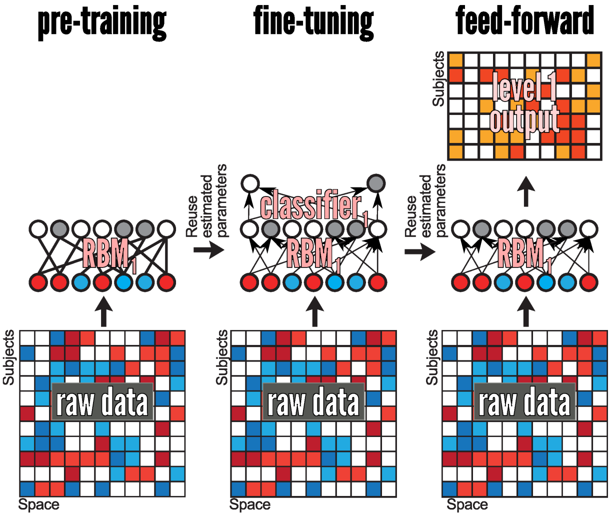
Deep Belief Network

- stack RBMs
- regulate the depth
- in this work we investigate a 3 layer network
- 50-50-100 hidden units



Converting RBM training into deeper models



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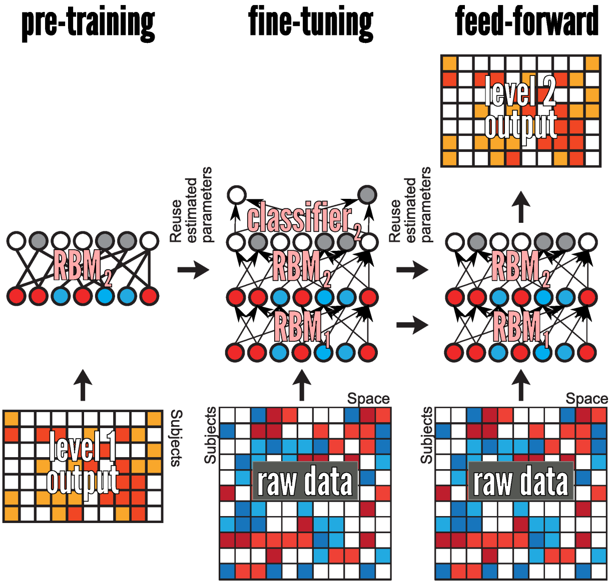

Depth helps classification (numbers)

- A combined MRI dataset from schizophrenia studies at[4]:
  1. Johns Hopkins University (JHU),
  2. the Maryland Psychiatric Research Center (MPRC),
  3. the Institute of Psychiatry, London, UK (IOP), and
  4. the Western Psychiatric Institute and Clinic (WPIC).
- 198 schizophrenia patients and 191 matched healthy controls;
- 10-fold cross validation of classification performance

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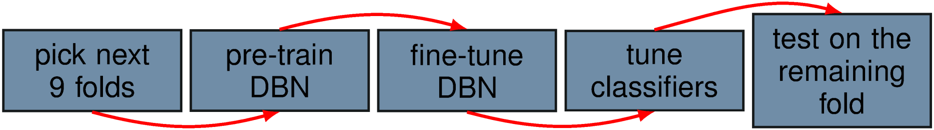

depth	raw	1	2	3
SVM F-score	0.68 ± 0.01	0.66 ± 0.09	0.62 ± 0.12	0.90 ± 0.14
LR F-score	0.63 ± 0.09	0.65 ± 0.11	0.61 ± 0.12	0.91 ± 0.14
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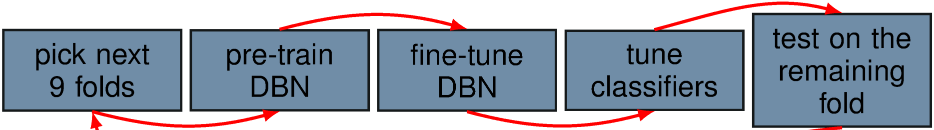

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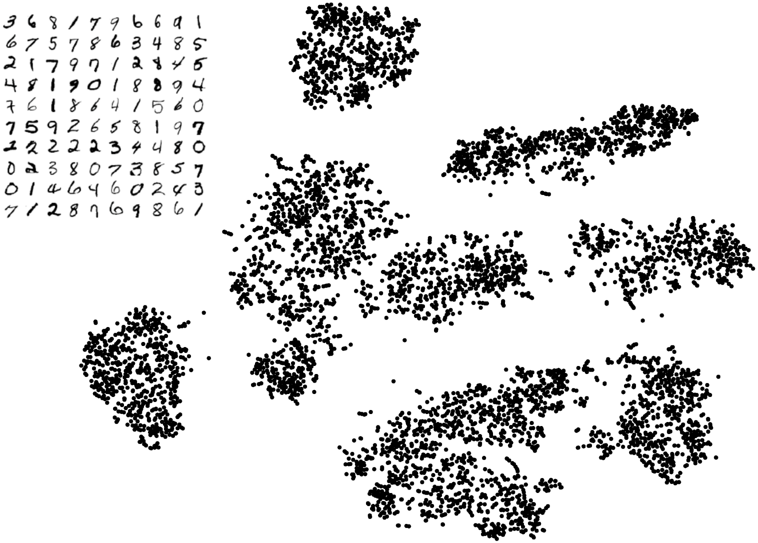

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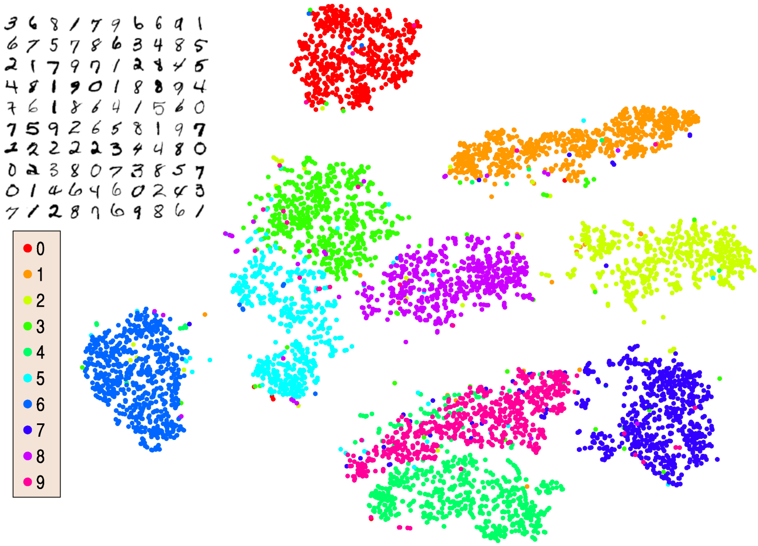

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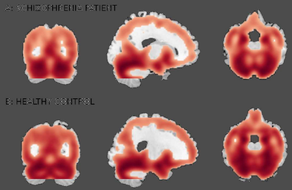
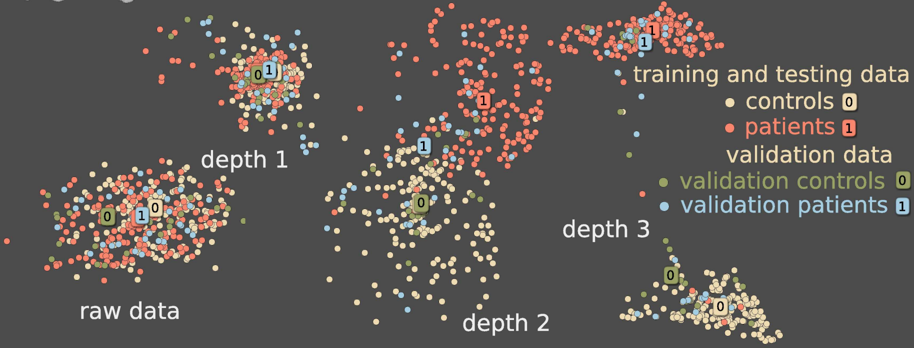
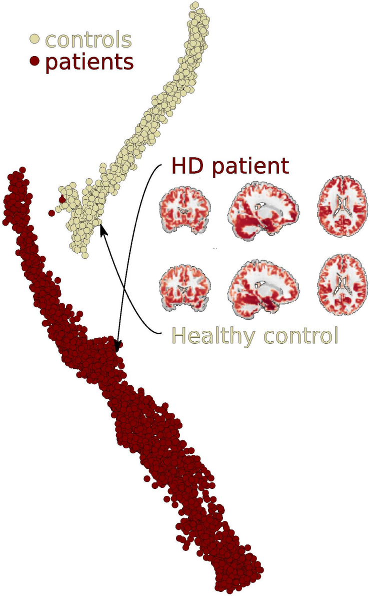
Depth helps classification (explanations)





..and given enough data depth helps discovery

- Huntington disease data[a]
- 3500 MRI scans
- 1200 subjects
- not doing classification
- using all data and the class label (patient/control) to learn representations
- mapping 100-dimensional third level features to a 2D map
- did deepnet learn something we did not tell it?
- disease severity!



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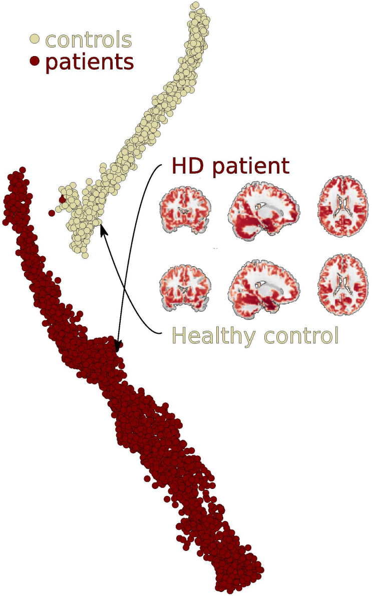

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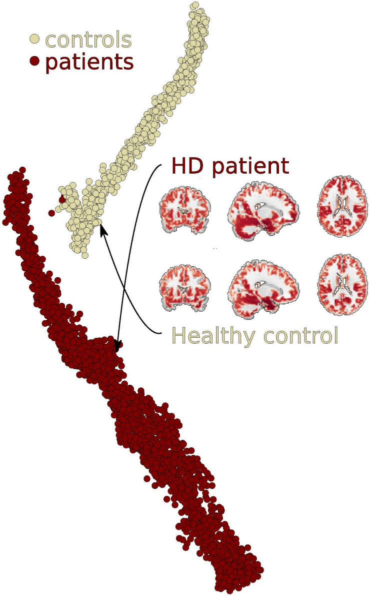

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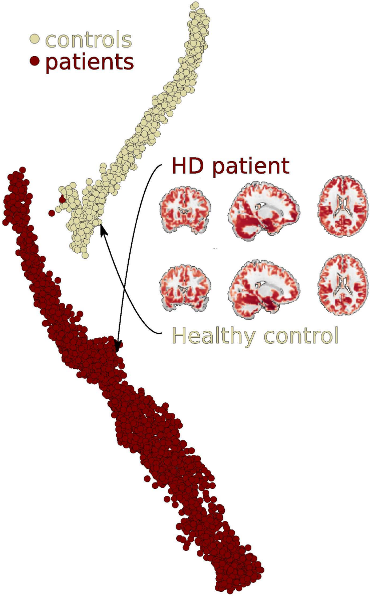

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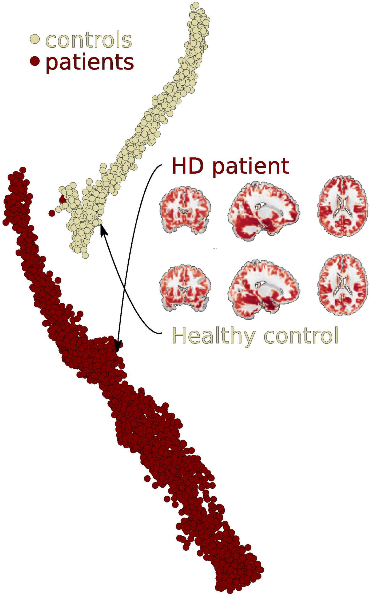

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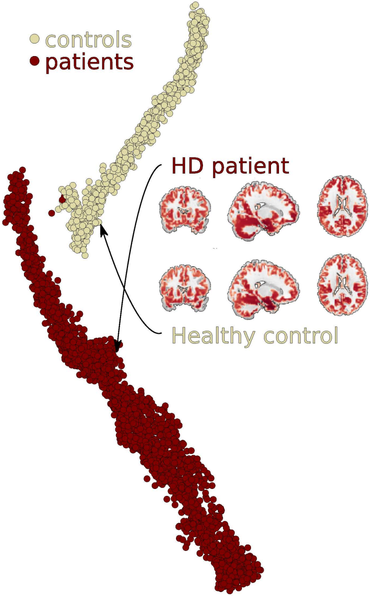

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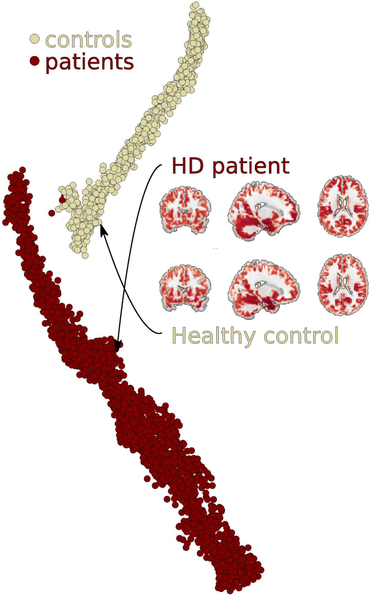

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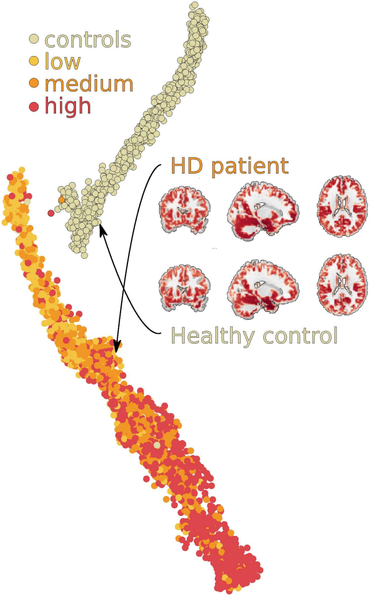

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Summary (the claims of deep learning hold)

- probabilistic building block works competitively[a]
- classification performance is great! and holds promise
- the deep belief net learns more with depth
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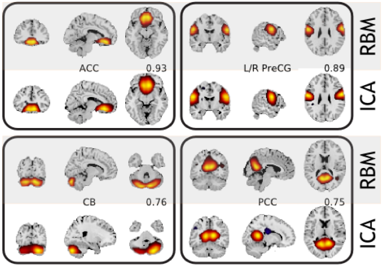

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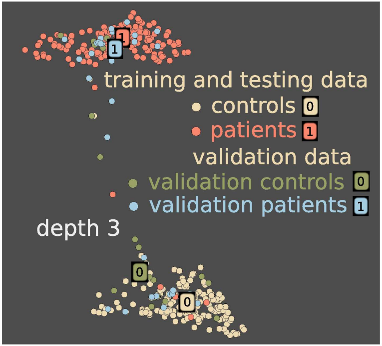

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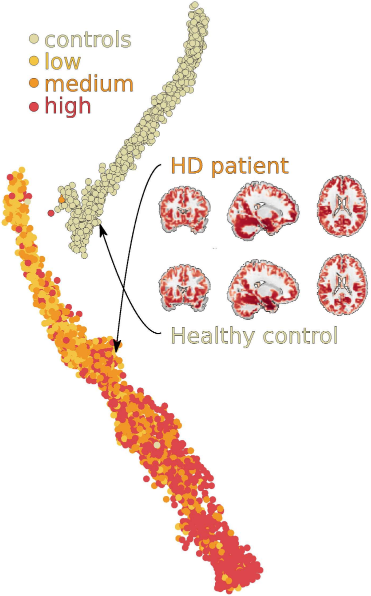

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Future work

- Learn to learn dynamic repesentations (temporal models)
- Take advantage of already developed multimodal approaches
- Better understand parameterization for various types of data
- Extend deep models to better model independence and nonnegativity
- Apply deep learning to unsolved or difficult problems
- Many more...

Thank you!